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AKSELI HILTUNEN

TRADING OF INDIVIDUAL INVESTORS

Master's thesis

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Tässä paperissa tutkitaan yksityissijoittajien käyttäytymistä osakemarkkinoilla. Tarkastelemme kolmea eri perspektiiviä yksityissijoittajien taloudelliselle hyödylle, jotta pystymme kattamaan aihealueen mahdollisimman laajasti ja tarjoamaan todisteita tieteelliselle tutkimukselle. Tarkastelua varten rakennamme mallin, jonka avulla tutkimme voidaanko osakkeiden tulevia tuottoja uutisten jälkeen ennakoida seuraamalla yksityissijoittajien käyttäytymistä ennen uutisten julkistusta. Tutkimus tarjoaa uudenlaisia löydöksiä osaksi laajempaa tutkimusta akateemisissa kirjoituksissa, joissa tutkitaan yksityissijoittajien käyttäytymistä osakemarkkinoilla.

Tutkimuksessa käytettävä data on peräisin Suomen Arvopaperikeskukselta ja se ulottuu vuoden 2006 alusta vuoden 2009 loppuun. Tilastollisen mallin luomiseksi laskemme muuttujan, joka kuvaa kumulatiivista yksityissijoittajien nettokaupankäyntiä, jota verrataan tuleviin kumulatiivisiin markkinaportfolion tuoton ylittäviin tuottoihin. Vertailu tehdään aikataulutettuja sekä yllätyksellisiä uutisia hyväksi käyttäen ja lopuksi mallin paikkansapitävyyttä arvioidaan tarkastelemalla yksityissijoittajien käyttäytymisen ja tulevaisuuden tuottojen välistä yhteyttä ilman uutisia.

Tulokset osoittavat, että yksityissijoittajien kumulatiivinen nettokaupankäynti ennen uutista ennustaa osakkeen tulevia kumulatiivisia tuottoja uutisen jälkeen. Korrelaatio on kuitenkin heikko ja se riippuu suuresti käytettävien muuttujien aikaikkunoista. Lisäksi saamme eriäviä tuloksia kun tarkastelemme kaikkia yksityissijoittajia tai ainoastaan kaikkein aktiivisimpia yksityissijoittajia. Yksityissijoittajien kumulatiiviset netto-ostot ennen tulosjulkistuksia ennustavat positiivisia markkinaportfolion tuoton ylittäviä tuottoja julkistuspäivänä sekä heti tätä seuraavana päivänä. Tämän jälkeen tuotot kuitenkin kääntyvät negatiivisiksi. Yllättävien uutisten ympärillä vastaavanlaista korrelaatiota ei havaittu kun tarkasteltiin kaikkia yksityissijoittajia, mutta aktiivisten sijoittajien käyttäytyminen ennen yllättävää uutista korreloi osakkeen kumulatiivisten tuottojen kanssa kun käytetään kuukauden mittaista tarkastelujaksoa uutisen jälkeen. Kun uutiset jätettiin kokonaan tarkastelun ulkopuolelle, löydettiin todisteita siitä, että yksityissijoittajat tekevät taloudellisesti järkeviä sijoituspäätöksiä.

ABSTRACT

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This study investigates the financial performance of individual investors in the stock market. We consider three different perspectives of financial performance of individual investors to offer significant evidence associated to the issue. We build a model to study whether or not the trading of individual investors before an event is predicting the short-term abnormal returns of the stock after the event. This study is providing further evidence to the growing academic literature about individual investors' performance.

The analyses are performed on data set provided by Finnish Central Securities Depository (FCSD) for four years from 2006 to the end of 2009. Performing statistical analysis, the individual net trading and cumulative individual net trading are calculated. Two different data sets are created to analyze the abnormal returns of individual investors around scheduled new and to analyze the same connection around non-scheduled news.

The results suggest that cumulative net individual trading prior to an event does predict the cumulative abnormal returns after the event but the link is quite weak and varies when different time-horizons are used or only active individual investors are considered. The results show a positive correlation between individual investors buying stocks prior to earnings announcement and the positive abnormal returns of the stock on the day of the event and on the following day. This correlation turns to be negative when we consider longer time periods for abnormal returns. With non-scheduled news, we did not find such correlation when considering all individual investors but correlation was found when we considered only the most active individual investors. When we did not control for any kind of events, we found that individual investors seem to be investing in an informed way.

PREFACE

I was finally able to complete the last missing piece that has been holding me from graduation. I want to thank my girlfriend Minna who has been extremely patient during the process.

Helsinki, 25.8.2014

Akseli Hiltunen

TABLE OF CONTENTS

1. INTRODUCTION 1
1.1 Research Background 1
1.2 Research Questions, Objectives and Exclusions 2
1.3 Structure of the Thesis 3
2. LITERATURE REVIEW 4
2.1 Characteristics of individual investors 5
2.1.1 Overconfidence 5
2.1.2 Sensation seeking 6
2.1.3 Familiarity 7
2.1.4 Asymmetric information 8
2.1.5 The representativeness bias 8
2.2 The Trading Patterns of Individual Investors 9
2.2.1 Contrarian trading 9
2.2.2 Diversification 10
2.2.3 The disposition effect 11
2.2.4 Reinforcement learning 12
2.2.5 Paying attention 13
2.3 The Performance of Individual Investors 14
2.3.1 Short-term Performance 14
2.3.2 Long-term performance 16
2.3.3 Cross-sectional performance 17
2.3.4 Summary of the studies 20
3. RESEARCH METHOD 23
3.1 Data and Sample 23
3.2 Theoretical Models and Methods 25
3.2.1 Linear Regression 25
3.2.2 Event Study 26
4. RESULTS 29
4.1 Individual net trading as a predictor for abnormal returns 29
4.2 Cross-sectional performance of individual investors 37
5. DISCUSSION 45
6. CONCLUSION 48
7. BIBLIOGRAPHY 50

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1. INTRODUCTION

1.1 Research Background

The behavior of stock markets and investors has been intensively studied for almost as long as the stock market has existed. Stock market behavior has been explained by investors' behavior and vice versa. After the 1950s, fundamental changes made way for the modern finance. First came the rational expectations revolution that was based on the assumption of investors being totally rational. This theory eventually led to the modern behavior finance that does not assume investors to be rational but rather irrational.

The current literature has started to be more and more interested of the individual investors, but there is still a lot of inconsistent results. Academic research is recognizing several different characteristics that are common to individual investors. This thesis is going to discuss the most common ones. Individual investors are seen as overconfident investors which mean that individuals have biased understanding of their investment skills. They also have a tendency to seek for sensations which may contribute to excessive risk-taking. They prefer familiar stocks over the unfamiliar ones and they possess asymmetric information. Finally, they are prone to the representativeness bias which means that they commonly have a tendency to irrationally attribute one characteristic to imply another.

These characteristics are causing individual investors to have certain recognizable trading patterns. However, the literature is not as concerned as it is with the characteristics described above. Still, most of the studies report that individual investors exercise contrarian trading and that they are dispositioning themselves. They also commonly fail to diversify their portfolios which is resulting to poor returns in contrast to the risk. Also, they engage to reinforcement learning meaning that they repeat previously taken actions that have yielded to desirable outcomes. Finally, they have limited attention span which means that they are using the information that is easily available rather than seeking for the information that they really need.

Besides certain trading patterns, the characteristics of individual investors are affecting the returns that they earn with trading. Academic research has been studying the short-term performance, long-term performance, and also the cross-sectional performance of individual investors. This is the research subject that is really splitting the literature in half. Some papers are reporting abnormal short-term returns while others papers are reporting negative abnormal returns. Same thing goes with the long-term performance and cross-sectional performance.

1.2 Research Questions, Objectives and Exclusions

The objective of this thesis is to study the financial performance of individual investors. The main research question to be answered in this thesis can be stated as follows:

Does individual investors' trading around company news predict short-term returns?

The main research question breaks down to the following three questions:

Does the trading of individual investors prior to company news predict the following short-term returns?

Do individual investors earn abnormal returns around company news?

Do individual investors earn abnormal returns around company news?

In other words, the main objective of this thesis is to answer whether or not individual investors should be trading when only the direct financial gains and losses from the trading are taken into account and all other possible motives for trading are ignored. Financial performance is investigated from three different perspective to provide significant evidence related to the issue.

This study is limited to only direct returns from trading. Also, we totally ignore all transaction costs even though they are directly caused by trading. This is done for several reasons:

1. We do not know the actual transaction costs as they vary greatly from investor to another.
2. Most of the current academic literature is investigating transaction costs separately from the direct returns of trading.
3. Transaction costs are not unambiguous as they might have, for example, tax effects.

We are only studying Finnish individual investors as it is not possible to us to recognize foreign individual investors from other foreign investors.

There are four limitations that were recognized during this study:

1. This study is limited to only direct returns from trading.
2. All transaction costs are ignored even if they are directly caused by trading.
3. A large set of data exceeding four years may produce concrete results and support the findings of this study.
4. OLS is the simplest econometric technique. Given the complexities of data set, a more sophisticated econometric may produce further elaborative results.

1.3 Structure of the Thesis

The thesis is divided in to six chapters. The first chapter is the introduction to the subject. This chapter will give the reader an overview of what the paper is containing and how it is structured. After this chapter the reader knows what is expected to be found from this paper.

The second chapter entails the literature review looking in to individual investors. We investigate the characters, trading patterns and the financial performance of individual investors. The aim of the literature review is to get a good idea on the setting of the thesis as well as understanding the central concepts related to individual investors. The literature review also acts as the theoretical foundation for the empirical part of the study.

After the literature review the research method is introduced. This part explains the methodologies used to build the empirical part of the study. The chapter presents the data used for this study and describes the theoretical models and the ways that the data was then analyzed.

The results are presented in chapter four. Under 4.1, individual net trading as a predictor for abnormal returns is examined while 4.2 shows the analysis of cross-sectional performance of individual investors. Both sub sections reveal the incremental changes made to the framework to broaden the analysis.

The fifth chapter depicts “Discussion” which is based on the findings of previous chapter. Section 5.1 discuses predictive power of net individual trading and investors’ performance while section 5.2 encompasses cross-sectional differences.

The final chapter concludes the thesis and presents limitation in the study.

2. LITERATURE REVIEW

Prior to the early 1950s, the finance literature was mainly descriptive and contained institutional detail. After that, fundamental changes began to take place which made modern finance become prominent. (Ardalan, 2004) In the 1970s, rational expectations revolution was in its first blush of enthusiasm and the efficient markets theory was born (Shiller, 2003). Before that time, academic work had mainly focused on forecasting future returns from past returns (Fama, 1991). The efficient markets theory, however, was completely different from the ones before that. According to Shiller (2003), prominent finance models of the 1970s were connecting asset prices to economic fundamentals. They used rational expectations to tie together finance and the entire economy in to single theory. (Shiller, 2003)

It did not take too long before the first anomalies in the efficient markets theory were reported and some of these anomalies can already be found from the finance journals of the 1970s. Still, it was not before the 1980s when the discussion of the consistency of the efficient markets model for the aggregate stock market started. More anomalies were found from the theory and finally in the 1990s the focus of academic discussion shifted away from the econometric analyses of time series on prices, dividends and earnings. This gave birth to the field of behavioral finance which concentrates to developing models of human psychology as it relates to financial markets. (Shiller, 2003) This models are not perfect either but they are very useful when studying individuals as investors.

In the literature, there is substantial amount of studies related to individuals as investors. Many of these studies present individual investors as noise investors. They find that individuals are not investing in a manner suggested by the traditional efficient market theories where investors are risk-averse and rational. Explanations for this behavior range from low-IQ to seeing trading as entertainment. Some studies also suggest that individuals could realize that they have disadvantage but trade for non-speculative reasons like liquidity needs, rebalancing and taxes. Whatever the reason, individual investors seem to earn poor return from direct stock investments which raises a question that why do so many investors directly invest in common stocks when they could earn better returns with lower risk in low-cost mutual funds, such as index funds.

In this literature review, we find that individual investors have certain characteristics that are, at least partly, influencing the trading patterns of individual investors that eventually determine their performance. These characteristics are presented in the chapter 2.1. Chapter 2.2 is presenting the empirically found trading patterns that are discussed in the academic literature. Finally, chapter 2.3 is providing evidence of the performance of individual investors.

2.1 Characteristics of individual investors

2.1.1 Overconfidence

There is a rich literature in psychology stating that people, in general, are overconfident[1]. Chuang and Susmel (2011) have studied the overconfidence between institutional and individual investors in Taiwan and found out that individual investors are more overconfident traders than institutional investors. For this reason, the high turnover and low diversification described in the previous chapter, can be partly due to overconfidence of individual investors.

According to Moore and Healy (2008), there is three distinct ways (types of overconfidence) to define overconfidence in the research literature: (1) over estimation of one's actual performance, (2) overplacement of one's performance relative to others, and (3) excessive precision in one's beliefs. One example of over estimation of one's actual performance is a student who might think that he scored 80% on a test when he actually scored 65% and the average score was 90%[2]. Svenson (1981) provides an example of the overplacement of one's performance relative to others. He studied a group of students from Sweden and from the United States and recorded that "a majority of subjects regarded themselves as more skillful and less risky than the average driver in each group respectively". (Svenson, 1981) A classic illustration of excessive precision in one's beliefs is an experiment where subjects are presented a series of 10 difficult questions (e.g. "How high is the Eiffel tower?"). They are then asked to provide intervals (high and low guess) such that the correct answers are within the intervals with a probability of 90%. Highly rational subjects would provide intervals that contain the right answer nine times out of then but Alpert and Raiffa (1982) found that typically subjects provided intervals that contained far fewer correct answers.

Extensive research on overconfidence has also lead to the development of theoretical models that are based on the observation that investors are overconfident[3]. Most of these models assume that investors are over estimating their own actual performance (type 1 overconfident) and there has been empirical work trying to find out the type of overconfidence that is linked to excessive trading. Dorn and Huberman (2005) found that investors prone to type 2 overconfidence are trading more than their peers. On the other hand, Glaser and Weber (2007), using a survey study, did not find a link between excessive

[1] See e.g. (Alicke and Govorun, 2005, Allison et al., 1989, Barber and Odean, 2000, Burson and Klayman, 2005, Chen et al., 2007, Dawes and Mulford, 1996, Fischhoff et al., 1977)
[2] See Moore and Healy (2008) for discussion.
[3] See e.g. (Benos, 1998b, Caballé and Sákovics, 2003, Daniel et al., 1998, Gervais and Odean, 2001, Hong et al., 2006, Kyle and Wang, 1997, Odean, 1998c, Peng and Xiong, 2006, Scheinkman and Xiong, 2003, Wang, 2001)

trading and type 2 overconfidence. Finally, Grinblatt and Keloharju (2009) found that investors with type 1 overconfidence have the tendency to trade more.

Benos (1998a) and Odean (1998c) propose in their theories that, due to their overconfidence, investors trade too much. This hypothesis is tested by Odean (1998b) who finds that overconfident investors possibly trade even when their expected gains are not enough to offset trading costs which states that overconfident investors are trading too much. At the same time, Barber and Odean (2000) found evidence that investor who trade the most also perform the worst. Together these evidences imply that overconfident investors would perform worse than their pier in the stock markets. There is even empirical evidence that men, who are more prone to be overconfident than women, are generally trading more and for that reason performing worse than women (Barber and Odean, 2001).

2.1.2 Sensation seeking

Another explanation to for excessive trading of individual investors is that trading appeals to same kind of people that enjoy gambling. This would imply that traders may be seeking for sensations and it would affect their trading. Gamblers are looking for excitement more than rational investments which intuitively means trading stocks with high volatility and probably trading more than other risk-averse investors. Some evidence can be found from literature that are providing background for this theory.

Dorn and Sengmueller (2009) studied 1000 German brokerage clients by matching their trading records to survey responses. They document that "entertainment-driven investors trade even though trading diminishes the expected monetary payoff of their portfolio". According to their study, the most entertainment-driven traders are trading about twice as much as their peers who fail to take pleasure from gambling and investing. (Dorn and Sengmueller, 2009)

Grinblatt and Keloharju (2009) also found similar evidence. They used Finnish dataset and analyzed both sensation seeking and overconfidence as factors leading to trading. They used dataset from Finnish Armed Forces that contained records of candidates' actual ability together with perceived ability. For sensation seeking, traffic tickets were used as a proxy stating that those who speed have higher probability to be sensation seekers. They report that both sensation seeking and overconfidence are affecting trading but the results are slightly different whether one focuses on the decision to trade, the number of trades, or portfolio turnover as the dependent variable of interest. (Grinblatt and Keloharju, 2009)

Dorn et al. (2014) are studying whether or not playing the lottery and gambling in financial markets can be substitutes for each other. In the United States, increases in the jackpots of the multistate lotteries are associated with significant reductions in small trades in the stock market. Consistent with that, also California-based and discount brokerage clients and German discount brokerage clients are significantly less likely to trade during week with higher lottery prizes in California and German lotteries. Speculative trading is affected in more lottery-like securities like stocks and options but not in bonds and mutual funds. They also argue that the negative relation between trading activity and jackpots is stronger for individuals who are more likely to play the lottery. (Dorn et al., 2014)

2.1.3 Familiarity

There is a growing number of studies that have found evidence of informed individual investors i.e. individual investors earning abnormal returns[4]. But how could individual investor gain advantage against Wall Streets' industry experts with excessive resources? Familiarity is an intuitive explanation that might be giving individual investors little advantage against institutional investors. On the other hand, it might also be working against individual investors and cause a cognitive bias that Kahneman (2011), p. 90 named WYSIATI (What You See Is All There Is). This could bias investment decisions towards familiar stocks simply because the knowledge of other stocks is missing.

Massa and Simonov (2006) used a unique dataset of Swedish investors to study the question of whether investors use their investment in financial assets to hedge their non-financial income. They document that investors do not engage in such a hedging but seem to tilt their portfolio toward stocks that are most closely related to them. However, they argue that this familiarity-driven behavioral is not a biased but based on information and allows the conditioning on a cheap source of information for the investors. This gives familiarity-based investors information advantage and allows them to earn relatively higher returns. (Massa and Simonov, 2006) Similarly, Ivković and Weisbenner (2005) argue that exploiting local knowledge does generates higher returns. They analyzed data on the investments a large number of individual investors made through a discount broker from 1991 to 1996. They document that households exhibit a strong preference for local investments and the average household generates an additional annualized return of 3.2% from its local holdings relative to its nonlocal holdings. (Ivković and Weisbenner, 2005)

Contrarian to two studies discussed above, Seasholes and Zhu (2010) document that portfolios of local holdings do not generate abnormal performance. They even found that purchases of local stocks significantly underperform sales of local stocks. This underperformance remains when focusing on stocks with potentially high level of information asymmetries. They conclude that individuals do not help incorporate information into stock prices. Døskeland and Hvide (2011) found even more conflicting evidence with information-based investing in local stocks. They conclude that, after excluding own-company stock holdings, individual investors in Norway are overweighting stocks in the industry that they are working for and earn negative abnormal returns by doing so. (Døskeland and Hvide, 2011)

[4] See chapter 2.3.1

2.1.4 Asymmetric information

Barber and Odean (2011) are providing one alternative explanation for individual investors' behavior. According to them it is possible to that individual investors realize that they are at an informational disadvantage when trading and only do so for non-speculative reasons including liquidity needs, rebalancing, and taxes. When faced with these needs, individual investors are forced to trade with other investors who might be better informed. On the other hand, it is hard to believe that the high annual turnovers reported by Barber and Odean (2000), Barber et al. (2009a) and Gao (2002). They also argue that investors who do have unusual non-speculative needs to trade could dramatically lower their asymmetric information and transaction costs by investing in low cost, no load mutual funds. (Barber and Odean, 2011)

Similarly, Barber et al. (2009a) are listing reasons for uninformed individuals to trade. These are liquidity requirements, rebalancing needs, hedging demands, entertainment and overconfidence. They add that the turnover in Taiwan is about 300 percent annually and two to three times that observed in the United States. It seems unlikely that the hedging needs in Taiwan are two to three times those in the United States. They also report that "From 1940 through 1970, annual turnover on the NYSE was a mere 16 percent. It is similarly implausible that the liquidity, rebalancing, and hedging needs of contemporary U.S. investors are six times that of U.S. investors during the mid-twentieth century. Undoubtedly, a great deal of current trading in Taiwan and the U.S. is speculative". (Barber et al., 2009a)

2.1.5 The representativeness bias

Tversky and Kahneman (1974) define the representativeness bias as the tendency to irrationally attribute one characteristic to imply another. In other words, the representativeness bias is a reliance on stereotypes to form quick and otherwise irrational opinions (Shefrin, 2008, p.7). One example of this bias would be an assumption that some person is studying computer sciences only because he or she looks skinny and has nerdy classes. Next we discuss some relevant literature related to this type of bias.

Using brokerage account data in China, Chen et al. (2007) studied investment decision making in an emerging market. Among other findings, they argument that Chinese investors seem to believe that past returns are indicative of future returns. (Chen et al., 2007) Similar results are documented by Chang et al. (2009) who studied Super Bowl commercial likeability and conclude that liked commercials coincide with higher stock returns which is consistent with the representativeness bias.

2.2 The Trading Patterns of Individual Investors

2.2.1 Contrarian trading

Number of studies have found evidence of individual investors being contrarian traders[5]. By definition, contrarian traders are buying stocks when their prices are declining and selling them when the prices are inclining. According to Dhar and Kumar (2001), contrarian traders are more likely to buy stocks at near month low prices and to sell stocks at near month high prices. Contrarian traders are also reluctant to sell loser stocks which might be because of the hope for price reversals. (Dhar and Kumar, 2001) However, Linnainmaa (2010) documents that individuals' short-term contrarian behavior is mostly due to limit orders and that the trading records distort inferences about investor's intentions due to how limit orders work.

Kaniel et al. (2008) argue that there is a widespread agreement in the literature that individual investors tend to be contrarian. Their own study also contributes to this believe. They used a data set provided by the New York Stock Exchange and found that individuals tend to buy stock following price declines in the previous month and to sell following price increases in the previous month. Along with other evidence found, they argue that this type of pattern is consistent with the notion that risk-averse individual investors provide liquidity for institutional investors to meet their demand for immediacy. (Kaniel et al., 2008)

Grinblatt and Keloharju (2000) also found evidence of individual investors being contrarian. They used a data set from the central register of shareholdings for Finnish stocks in the Finnish Central Securities Depository and found that most sophisticated institutional investors tend to pursue momentum strategies while less sophisticated investors seem to be contrarian. Investors categorized as less sophisticated investors are, in this study, households i.e. individual investors while the most sophisticated investors are foreign institutions. (Grinblatt and Keloharju, 2000)

Study conducted by Barber et al. (2009c) extends the evidence of contrarian trading of individuals in an interesting way. They also report that individual investors sell stocks with strong past returns but also that they buy them. However, the relationship between selling stocks and strong past return is stronger at short horizons (one to two quarters) and the relationship between buying stocks and strong past returns is stronger at long horizons (up to 12 quarters). (Barber et al., 2009c) This implies that individual investors are contrarian traders of stocks with strong past returns over recent periods but not over longer periods.

[5] See e.g. (Barber and Odean, 2000, Barber et al., 2009c, Griffin et al., 2003, Grinblatt and Keloharju, 2000, Jackson, 2003, Kaniel et al., 2008, Richards, 2005)

2.2.2 Diversification

According to Markowitz (1952), the father of modern portfolio theory, risk averse investors should have well diversified portfolios to minimize the variance of portfolio return, given expected return, or to maximize expected return, given variance. It is intuitive to think that institutional investors would have more diversified portfolios than individuals because of the larger investment amounts. Institutional investors are beyond the scope of this thesis but the literature seems to provide evidence against well diversified portfolios of individual investors.

Quite a few studies have found that investors are prone to invest in domestic stocks opposed to foreign stocks even though those would provide the investor with strong diversification benefits[6]. On the other hand, French (2008) reports that US investors' have grown the portion of foreign stocks in their portfolios from 2% in 1980 to 8.5% in 1990 and 27.2% in 2007. Solnik and Zuo (2012) are adding that even though home bias is globally extensive it varies greatly between countries. One possible explanation for the preference of domestic stock could be familiarity that was discussed in more detail in the chapter 2.1.3 where some evidence was presented that individual investors are prone to invest in local stocks. Investing in local stocks is problematic in the perspective of diversification because it exposes the investor to idiosyncratic local risks that are also likely to be correlated with their job perspectives (Barber and Odean, 2011).

Barber and Odean (2000) studied 66 465 households at a large discount brokerage firm in the United States and found that individual investors only hold four stocks on average and turned over 75 percent of its common stock portfolio annually. They are, on average, also biased to make common stock investments toward small value stocks with high market risk. (Barber and Odean, 2000) Mitton and Vorkink (2007) are providing evidence that failure to diversify could be largely explained by the fact that investors sacrifice mean-variance efficiency for higher skewness exposure. Kumar (2009) shows that at the aggregate level, individual investors prefer stocks with lottery features i.e. stocks that have low price, high idiosyncratic skewness and high idiosyncratic volatility. These findings are providing background for the results of Goetzmann and Kumar (2008) that individual investors are holding to portfolios that are highly volatile. They also report that portfolios of individual investors consists of stocks that are more highly correlated than stocks in a portfolio that has been constructed of randomly chosen stocks. (Goetzmann and Kumar, 2008)

Goetzmann and Kumar (2005) examined the diversification decisions of more than 60,000 individual investors during a six year period (1991-96) in recent U.S. capital market history. Majority of these investors were under-diversified and the extent of under-diversification is more severe in retirement accounts. Investors' personal characteristics,

[6] See e.g. (Cooper and Kaplanis, 1994, French and Poterba, 1991, Lewis, 1999, Tesar and Werner, 1995)

stock preferences and behavioral biases all affect their diversification choices. They argue that "Younger, lower-income (less wealthy), and relatively less sophisticated investors and those who follow price trends, prefer local (familiar) stocks, and exhibit over-confidence hold relatively less diversified portfolios" and that results support the asymmetric information hypothesis for under diversification. (Goetzmann and Kumar, 2005) Grinblatt et al. (2011) document that low-IQ individuals have often fewer stocks, are less likely to include a mutual fund, and generate more diversifiable risk in their portfolios than higher-IQ investors. Goetzmann and Kumar (2008) find similar results as they argue that under-diversification is more prevalent among less-sophisticated investors.

2.2.3 The disposition effect

Shefrin and Statman (1985) define the disposition effect as a positive theory of capital gain and loss realization in which investors tend to sell winners (stocks that have increased in value since bought) too early and ride losers (stocks that have decreased in value since bought) too long. There is a wide range of literature analyzing the disposition effect [7] and many of the studies have found that the disposition effect is affecting both individual and institutional investors but that it is affecting individual investors more. Next we discuss few of the related studies that focus on individual investors in greater depth.

Odean (1998a) analyzed trading records of 10,000 accounts from 1987 through 1993 at a large discount brokerage house in the United States and argues that, in general, investors realize their gains more readily than their losses. His analysis also shows that many investors engage in tax-motivated selling, especially in December. (Odean, 1998a) Similarly, Grinblatt and Keloharju (2001) used a dataset from the central register of shareholdings for Finnish stocks and also found evidence of individual investors being reluctant to realize losses, engaging in tax-loss selling activity, and that past returns and historical price patterns affect trading of individual investors.

Feng and Seasholes (2005) are providing further insight to the disposition effect as they studied how investors' sophistication and trading experience affect the behavioral biases in financial markets. Particularly, they are paying attention to the disposition effect and they report that "Together, sophistication (static differences across investors) and trading experience (evolving behavior of a single investor) eliminate the reluctance to realize losses. However, an asymmetry exists as sophistication and trading experience reduce the propensity to realize gains by 37% (but fail to eliminate this part of the behavior.)" (Feng and Seasholes, 2005) Using a dataset containing the disaggregated wealth of all households in Sweden, Calvet et al. (2008) found similar results as they studied the dynamics

[7] See e.g. (Barber et al., 2007, Barber and Odean, 2011, Brown et al., 2006, Calvet et al., 2008, Chen et al., 2007, Dhar and Zhu, 2006, Feng and Seasholes, 2005, Frazzini, 2006, Grinblatt and Keloharju, 2001, Heath et al., 1999, Odean, 1998a, Shapira and Venezia, 2001, Weber and Camerer, 1998)

of individual portfolios. They conclude that the tendency to sell winning stock is weaker for wealthy investors with diversified portfolios of individual stocks. (Calvet et al., 2008) This seems to be in line with the evidence found by Feng and Seasholes (2005).

According to Odean (1998a), alternative explanations have been developed to explain why investors might realize their profitable positions while retaining their losing positions. One of them is that investors may believe that their current losers will in the future outperform their current winners. Other is that they may sell winners to rebalance their portfolios. It is also possible that they may refrain from selling losers due to the higher transactions costs of trading at lower prices. However, he reports that the disposition effect can still be observed even if the data are controlled for rebalancing and for share price. Still the winning investments that investors choose to sell continue to outperform the losers they keep. (Odean, 1998a) Disposition effect could also be partly due to limit orders of individual investors. Linnainmaa (2010) suggests that due to how limit orders work, investor trading records reflect mechanical effects that distort inferences about investor’s intentions. He also argues that approximately half of the disposition effect disappears as he excludes sales origination from limit orders from the study. (Linnainmaa, 2010)

2.2.4 Reinforcement learning

According to Barber and Odean (2011), the simplest form of learning may be to repeat behaviors that have previously caused pleasure and to avoid behaviors that have caused pain. Same type of behavior can also be found among individual investors. Next we discuss the findings of few relevant studies.

Strahilevitz et al. (2011) analyze detailed data from two brokers in the United States and document that investors are reluctant to repurchase stocks previously sold for a loss and stocks that have risen in price subsequent to prior sale. Evidence shows that investors are disappointed when they realize loss from a stock and regret having ever purchased the stock. Similarly, investors are disappointed if the stock they sold continues to rise and regret having sold the stock in the first place. Both of these negative emotions deter investors from repurchasing stocks that caused these emotions. Consistently with that, investors are repurchasing stocks whose previous purchase resulted in positive emotions. (Strahilevitz et al., 2011)

Quite a few interesting extensions can be found to the previously reviewed study of Strahilevitz et al. (2011). Huang (2012) used trading records for households at a large discount broker from 1991 to 1996 and found that the experience of positive excess returns in a given industry increases the probability of purchasing similar stocks in that industry relative to other industries. Furthermore, he document that investor sophistication mitigates this experience effect. (Huang, 2012) De et al. (2010) add that individual investors seem to trade more actively when they have positive experiences from the recent trades in the past. Malmendier and Nagel (2009) investigated whether individuals' experiences of macro-economic outcomes have long-term effects on their risk attitudes. They document that "individuals who have experienced low stock-market returns throughout their lives report lower willingness to take financial risk, are less likely to participate in the stock market, and, conditional on participating, invest a lower fraction of their liquid assets in stocks." (Malmendier and Nagel, 2009)

Reinforcement learning can have effects also for other types of investing besides common stocks. Choi et al. (2009) show that reinforcement learning is affecting the investment decisions of 401(k) savings. They document that investors who have experienced particularly rewarding outcomes from 401(k) saving increase their 401(k) savings rate more than investors who have less rewarding experiences. (Choi et al., 2009) There also seems to exist a strong positive link between past IPO returns and future subscriptions at the investor level in Finland (Kaustia and Knüpfer, 2008).

2.2.5 Paying attention

Barber and Odean (2011) report that individuals have a limited amount of attention they can devote to investing. There is two distinct ways that attention can affect the trading behavior of investors: 1) directing too little attention to relevant information can delay the reaction to important information, 2) directing too much attention to information can lead to an overreaction. (Kaustia and Knüpfer, 2008) Next we discuss the studies that provide evidence for the notion that distracted investors miss important information.

According to Barber and Odean (2008), attention has a strong impact to the individual investor buying decision. This is mainly because investors counter a huge search problem when looking for stocks to buy. Due to limited resources, investors are prone to consider only stocks that first catch their attention. Same is not true for the selling decision because individual investors are usually only selling stocks that they already own and, since they usually own only very limited amount of stocks, the decision to sell is less sensitive to attention effects. (Barber and Odean, 2008) Similarly, Seasholes and Wu (2007) are studying stocks in the Shanghai market and argue that attention-grabbing events lead active individual investors to buy stocks they have not previously owned. Engelberg and Parsons (2011) also document similar results as they state that "For all earnings announcements of S&P 500 Index firms, we find that local media coverage strongly predicts local trading, after controlling for earnings, investor, and newspaper characteristics. Moreover, local trading is strongly related to the timing of local reporting, a particular challenge to non-media explanations."

Hirshleifer et al. (2009) studied investor distraction hypothesis with firms' earnings announcements and document that "the immediate stock price and volume reaction to a firm's earnings surprise is weaker, and post-earnings announcement drift is stronger, when a greater number of earnings announcements by other firms are made on the same day." DellaVigna and Pollet (2009) are comparing the responses to earnings announcements on Friday to the response on other weekdays. They assume that investor inattention is more likely on Friday than any other day. They find that Friday announcements have 15% lower immediate response and a 70% higher delayed response. (DellaVigna and Pollet, 2009)

Da et al. (2011) are using search frequency in Google as a measure of investor attention. They analyze sample of Russel 3000 stocks from 2004 to 2008 and argue that search frequency is correlated with investor attention and that it is likely to measure the attention of retail investors. They find that an increase in search frequency predicts higher stock prices in the next 2 weeks and an eventual price reversal within the year. Also it predicts large first-day return and long-run underperformance of IPO stocks. (Da et al., 2011)

2.3 The Performance of Individual Investors

2.3.1 Short-term Performance

Kaniel et al. (2008) are examining the short-horizon dynamic relation between the buying and selling by individual investors and both previous and subsequent returns. Using a dataset constructed from the NYSE's Consolidated Equity Audit Trail Data (CAUD), they measure order imbalance over a nine-week horizon and find that the top decile of stocks heavily bought by individual investors earn market-adjusted returns of 0.80% in the following 20 trading days. Similarly, the bottom decile of stocks heavily sold by individual investors earn excessive return of -0.33% in the following 20 trading days. This also means that the behavior of individual investors predicts the short-term movement of the stock price. They document positive excess returns in the month that follows intense buying by individuals and also negative excess returns after individuals sell. They also find evidence of individuals buying stocks after price declines in the previous month and sell after price increases. They argue that the patterns they have documented are consisted with the notion that risk-averse individual investors provide liquidity to meet institutional demand for immediacy. (Kaniel et al., 2008)

Kaniel et al. (2012) analyze the same data as Kaniel et al. (2008) but they focus on the trading of individual investors around earnings announcements because informed individual investors should be especially active at these times. Evidence shows that pre-event trading by individuals does in fact predict return on and after earnings announcement dates. They document that "stocks accumulated by individuals in the 10 days prior to earnings announcements exhibit abnormal returns that exceed the abnormal returns of stocks sold by individuals by about 1.47% in the two-day event window around earnings announcements. Moreover, we find a 5.45% average difference in the returns of these stocks in the three months after the event" They conclude that these results are consistent with the idea that individual investor trading in aggregate prior to earnings announcements contains pertinent information. Two explanations are provided for the potential information advantage of individual investors: 1) The aggregation of information through trades of many individuals results a signal that is very precise or, 2) individual investors may be better positioned to trade aggressively than institutions when they are informed and they also may be less constrained than institutions (Kaniel et al., 2012) Another possible explanation would be that individual investors are buying familiar stocks and like Massa and Simonov (2006) document that familiarity-driven behavior is not biased but based on information and allows the conditioning on a cheap source of information for the investors.

Divergent results for the two studies above is provided by Vieru et al. (2006) who use data from Finnish Stock Exchange covering the year 1996-2000. One of their hypothesis is that active individuals' trading before the announcement precedes post-announcement abnormal returns. Their study provides evidence for this hypothesis. They find that active investors increase buying (selling) relative to selling (buying) before positive (negative) news. (Vieru et al., 2006)

Kelley and Tetlock (2013) also study the role of retail investors in stock pricing using a dataset of over $2.6 trillion in executed trades coming from dozens of retail brokerages from 2003 to 2007. Like the studies discussed above, they also find that daily buy-sell imbalances of retail investors from both market orders and limit orders positively predict the cross-section of stock returns at monthly horizons. Market order imbalances correctly predict news about firm cash flows as measured by either the linguistic tone of DJ news stories or earnings surprises and these results hold at daily, weekly, monthly and yearly horizons. Finally, they document that limit order imbalances are contrarian to daily and intraday returns even though market order imbalances are not. (Kelley and Tetlock, 2013)

Similarly, Barber et al. (2009b) find that weekly small trade imbalances are positively correlated with contemporaneous returns and also forecast cross-sectional differences in returns for the subsequent week. Stocks bought (sold) by individual investors during one week have positive (negative) abnormal returns that week and in the subsequent weeks. These returns, however, reverse over the next several months. (Barber et al., 2009b) According to Barber and Odean (2011), it is difficult to attribute these patterns to liquidity provision as the order imbalance used by Barber et al. (2009b) is based on signed rather than all trades. This kind of signing yields order imbalance measures that are only based on liquidity demanders rather than on liquidity suppliers. They document that "the contemporaneous relation be-tween returns and order imbalance is positive in BOZ (what one would expect when order imbalance is based on liquidity demanders), but negative in KST (what one would expect when order imbalance is based on liquidity providers)". Barber et al. (2009b) argue that correlated sentiment-based trading of individual investors explains the combination of a positive relation between small trade order imbalance and short-horizon returns that are followed by return reversals at long horizons.

In contrast to the studies presented above, Barber et al. (2009a) find divergent results as they study Taiwanese trading data from 1995 to 1999. All orders on the Taiwan Stock Exchange are limit orders. They define aggressive limit orders to be buy limit orders with high prices and sell limit orders with low prices, both relative to unfilled orders at the last market clearing. Passive limit orders are buy limit orders with low prices and sell limit orders with high prices. 65% of all trades emanate from aggressive orders. They document that aggressive orders by individuals are in fact earning negative abnormal returns even though passive orders are profitable at short horizon. Also passive orders by individuals suffer modest losses at longer horizons. They also construct a portfolios that mimics the trading of individual investors and earn reliable negative monthly alphas of -11.0%, -3.3%, -1.9% over horizons of 1, 10, 25 days. (Barber et al., 2009a)

Andrade et al. (2008) also study data from Taiwan Stock Exchange and document losses for individual investors at short-horizon. They sort stocks into quintiles based on trading imbalances over the week. Stocks in the quintile that are bought the most earn return of -23 bps in the following week. Similarly, quintile sold the most earns returns of 29 bps in the following week. They report that “a single economic framework relying on a finite number of risk-averse liquidity providers explains several empirical relations between trading imbalances and stock prices”. (Andrade et al., 2008)

2.3.2 Long-term performance

Odean (1998b) use data from 1987 to 1993 of 10,000 investors at a large discount broker. He finds that the stocks bought by individual investors underperform the stocks sold by 23 basis points (bps) per month in the 12 months after the transaction. He also controls the experiment for the trades that have most likely been made for liquidity, rebalancing, or tax purposes but the results are persistent. (Odean, 1998b) According to Barber and Odean (2011), “these results are provocative on two dimensions. First, this is the first evidence that there is a group of investors who systematically earn subpar returns before costs. These investors have perverse security selection ability. Second, individual investors seem to trade frequently in the face of poor performance.”

Barber and Odean (2000) study 66,465 households with accounts at a large discount broker during 1991 to 1996. The message of the study is clear: trading is hazardous to individual investors’ wealth. Households are sorted into quintiles based on their monthly turnover during the sample period each quintile containing about 13,000 households. Average household earned 16.4% annual return which is 1.5% less than what markets return (17.9%). Also the difference in earnings between the quintile of most active investors and the quintile of most passive investors is significant. The most passive 20% of the investors earned 18.5% net of cost annual return while the most aggressive 20% of the investors earned only 11.4% net of cost annual return. (Barber and Odean, 2000)

Grinblatt and Keloharju (2000) are studying two years' worth of trading data from Finland. Their study is primarily focused on which investor groups exhibit momentum (the tendency to buy past winners and sell past losers) and which have the opposite, contrarian behavior but they also provide evidence of individual investors earning negative abnormal returns on long horizon as they study the performance of different categories of investors. Individual investors are net buyers of stocks with poor future performance (from day t+1 to day t+120). Similarly financial institutions and foreign investors are net buyers of the stocks with strong future performance.(Grinblatt and Keloharju, 2000)

Also Barber et al. (2009a) report that individual investor trading results in systematic and economically large losses. They use a complete trading history of all investors in Taiwan and construct portfolios that mimic the trading of individuals and institutions. When they construct portfolios based on the assumption that holding periods are ranging from one day to six months, the stocks bought by the individual investors perform poorly while the stocks sold by individual investors earn strong results. Aggregate portfolio of individuals earns annual abnormal returns of -3.8%. A strategy that mimics the buying and selling of individual investors and assumes a holding period of 140 trading days earns a negative abnormal return of 75 bps per month before accounting for transaction costs. Individual investor losses are about 2.2% of Taiwan's gross domestic product or 2.8% of the total personal income. (Barber et al., 2009a)

Hvidkjaer (2008) and Barber et al. (2009b) are both using signed small trades from TAQ database to study the trading of individuals in the United States. They both use small trades as a proxy for the trading of individual investors, and document that stocks heavily bought by individuals over horizons ranging from one month to one year underperform stocks heavily sold by individual investors. Hvidkjaer (2008) documents that at a formation period of six months, the top decile (stocks heavily bought) underperform the bottom decile (stocks heavily sold) by 89 bps per month. Similarly, Barber et al. (2009b) document that when measured annually, small trade order imbalance forecasts future returns; stocks heavily bought underperform stocks heavily sold by 4.4 percentage points the following year.

2.3.3 Cross-sectional performance

Grinblatt et al. (2012) analyze whether IQ influences trading behavior, performance, and transaction costs. They use equity return, trade, and limit order book data combined with two decades of scores from intelligence tests administered to nearly every Finnish male of draft age. Test scores range from 1 to 9 and the ones that scored 9 are classified as high-IQ and those who scored 1-4 are classified as low-IQ. They document that high-IQ investors are less subject to the disposition effect, more aggressive about tax-loss trading, and more likely to supply liquidity when stocks experience a one-month high. Investors with high IQ also exhibit superior market timing, stock-picking skill, and trade execution. The difference between portfolio returns earned by low-IQ versus high-IQ investors is

2.2% per year. However, the source of high-IQ investors' stock-picking skill is unresolved. (Grinblatt et al., 2012)

Korniotis and Kumar (2013) are studying the effects of cognitive abilities to the trading of individuals. They use a host of demographic variables (e.g. age, education, and social networks) to predict cognitive ability. They argue that smarter investors do earn positive abnormal annual returns of about 3% on risk-adjusted basis. Among investors with high portfolio distortions, smart investors outperform passive benchmarks by 2%. The difference in annual portfolio returns between smart and dumb investors is 5%. At the stock level, a portfolio of stocks with smart investor clientele outperforms the dumb clientele portfolio by 3.50% annually. They conclude that these results are suggesting that behavioral and information-based explanations for portfolio distortions apply to distinct subset of investors. (Korniotis and Kumar, 2013)

(Korniotis and Kumar, 2011) are extending the results above by using the same dataset. They study the investment decisions of older individual investors. They document "that older and experienced investors are more likely to follow "rules of thumb" that reflect greater investment knowledge. However, older investors are less effective in applying their investment knowledge and exhibit worse investment skill, especially if they are less educated, earn lower income, and belong to minority racial/ethnic groups. Overall, the adverse effects of aging dominate the positive effects of experience. These results indicate that older investors' portfolio decisions reflect greater knowledge about investing but investment skill deteriorates with age due to the adverse effects of cognitive aging." (Korniotis and Kumar, 2011)

Coval et al. (2005) are providing evidence of the strong persistence in the performance of trades of individual investors. They use a dataset provided by large discount brokerage firm from January 1990 through November 1996 to study this performance persistence. They find that the correlation of the risk-adjusted performance of an individual across sample periods is about 10 percent. They sort individual investors in to deciles and document that investors in the top performing decile in the first half of their sample subsequently outperform those in the bottom decile by about 8 percent per year. Strategies that buy the stocks bought by previously successful investors and sell the stocks bought by previously unsuccessful investors earn abnormal returns of 5 basis points per day. (Coval et al., 2005) However, this return spread does not account for transaction costs and Barber and Odean (2011) note that round-trip spreads and commissions would easily wipe out a 25 bps trading advantage.

Barber et al. (2011) are studying day traders in Taiwan. They use a dataset from Taiwan Stock Exchange over the period 1992 to 2006. They estimate that 450,000 individual investors engage in day trading on an average year and their combined trading accounts for 17% of total trading volume. They sort day trades based on their returns in year y and analyze their subsequent day trading performance in year $y+1$. They document that the

500 top-ranked day traders go on to earn daily before-fee (after-fee) returns of 61.3 (37.9) bps per day. At the same time, the bottom-ranked day traders go on to earn daily before-fee (after-fee) returns of -11.5 (-28.9) bps per day meaning that the spread between top-ranked and bottom-ranked day traders exceeds 70 bps per day. Even though some day traders are able to earn abnormal returns, they are a rare breed; less than 1% of the total population of day traders is able to predictably and reliably earn positive abnormal returns net of fees. (Barber et al., 2011)

Above we have seen studies that provide evidence of some individual investors outperforming others. If some individual investors are able to earn abnormal returns in contrast to others, one might assume them to be the professional fund managers with their personal portfolios. However, Bodnaruk and Simonov (2014) are providing evidence that this is not the case. They analyze the personal portfolios of mutual fund managers from July 2001 through June 2007. Interestingly enough, they do not find any evidence of that financial experts are making better investment decisions than their less financially astute peers. They do not earn higher returns, they do not diversify their risk better, nor do they exhibit lower behavioral biases. Mutual fund managers do much better in stocks they share with their mutual fund but only about 20% of them have any positions that are related to their mutual fund. (Bodnaruk and Simonov, 2014) This is clear evidence that day-to-day knowledge of financial markets does not help to earn higher returns but it does not imply that high-IQ investors could not outperform others.

Barber and Odean (2001) are testing the hypothesis that overconfident investors trade excessively. They do this by partitioning investors on gender because psychological research demonstrates that, in areas such as finance, men are more overconfident than women. Using data from February 1991 through January 1997 they document that men trade 45 percent more than women. On average, men have a turnover rate of about 80% while women have about 50%. While both genders are earning poor returns, this excessive trading reduces men’s net returns by 2.65 percentage points a year as opposed to 1.72 percentage points for women. Neither gender seems to have stock selection ability, so men’s tendency to trade more and the resulting trading costs are causing the difference in net returns. (Barber and Odean, 2001) Several other studies are also providing background for these kind of results[8]. (Dorn and Huberman, 2005) also find men to be more aggressive traders but they report that the gender effects are reduced when one accounts for differences in self-reported risk-aversion. In contrast to these studies, Feng and Seasholes (2008) are studying data from China and find no significant difference in turnover or performance between men and women.

[8] See e.g. (Agnew et al., 2003, Choi et al., 2002, Mitchell et al., 2006)

2.3.4 Summary of the studies

Table 1 present a summary of the studies.

Table 1: Summary of studies on individual investors' performance

Author(s)	Country	Main findings
Andrade et al. (2008)	Taiwan	Stocks bought by individual investors go to earn poor returns while stocks sold earn good returns.
Barber and Odean (2000)	US	Individual investors underperform the market. Active traders do worse than passive ones.
Barber and Odean (2001)	US	Women outperform men. Both genders underperform a market index.
Barber et al. (2009a)	Taiwan	Individual investors counter economically large losses.
Barber et al. (2009b)	US	Weekly order imbalance positively predicts returns at short horizon but negatively on long horizon.
Barber et al. (2011)	Taiwan	Only 1% of all day traders are able to earn positive returns after transaction fees.
Døskeland and Hvide (2011)	Norway	Individual investors prefer stocks in the industry they work for which leads to poor diversification and higher risk.
Dorn and Huberman (2005)	German	Risk tolerance is related to the diversification of portfolio. Investors who think that they know more than others trade more.
Feng and Seasholes (2008)	China	Turnover of men and women are equal and they earn similar returns.
Glaser and Weber (2007)	German	Investors who think that they know more than others trade more.
Grinblatt and Keloharju (2000)	Finland	Foreign investors outperform Finnish households.

Table 2: Summary of studies on individual investors' performance (Continued)

Author(s)	Country	Main findings
Grinblatt and Keloharju (2009)	Finland	Overconfidence and sensation seeking are linked to trading activity.
Grinblatt et al. (2011)	Finland	Investors with high IQ hold larger numbers of stocks and mutual funds more likely than others.
Grinblatt et al. (2012)	Finland	Trading of high-IQ investors predicts stock returns up to one month.
Huang (2012)	US	Investors are more likely to buy stocks in a industry where their previous investments have done well.
Hvidkjaer (2008)	US	Order imbalance over the last several months negatively correlates with the returns at horizon of 1 to 24 months.
Ivković and Weisbenner (2005)	US	Investors trading local company stocks earn strong returns.
Kaniel et al. (2008)	US	Trading of individual investors positively predicts short-term returns.
Kaniel et al. (2012)	US	Individual investors earn abnormal short-term returns after earnings announcements.
Kelley and Tetlock (2013)	US	Trading of individual investors positively predicts abnormal returns up to 20 days.
Korniotis and Kumar (2013)	US	Cognitive abilities predict variation in investor returns
Korniotis and Kumar (2011)	US	Older people do worse stock-picking decisions than younger people

Table 3: Summary of studies on individual investors' performance (Continued)

Author(s)	Country	Main findings
Linnainmaa (2010)	Finland	Individual investors do poorly on limit orders but still they earn strong returns on market orders.
Massa and Simonov (2006)	Sweden	Professionally or geographically familiar stocks help to earn abnormal returns
Odean (1998c)	US	Trading of individual investors negatively predicts short-term returns
Seasholes and Zhu (2010)	US	Findings of strong returns on local stocks are not robust to reasonable variations in methodology.
Vieru et al. (2006)	Finland	Trading of the most active individual investors prior to the earnings announcements predicts short-term returns.

As can be seen from the summary, most of the studies on individual investors are concentrated to the United States but there has been some studies also in Taiwan and Scandinavia.

3. RESEARCH METHOD

3.1 Data and Sample

This thesis is studying the trading of individual investors using data from three different main source. A data set provided by the Finnish Central Securities Depository (FCSD) contains every stock transaction of all Finnish investors on a daily basis for four years from 2006 to the end of 2009. These records represent the official central register of shareholdings for stocks and cover all of the companies represented in the Book Entry System. A data set provided by Kauppalehti provides us with the total trading volumes and closing prices for all of the stocks that are present in the FCSD's data set. The third data set is a handmade data set that contains information about news related to these companies.

Data from FCSD is comprehensive for Finnish investors since all of the Finnish investors who want to execute buy orders has to open an account in the FCSD's register which is where holdings and changes are filed. However, this does not apply to the foreign investors who are provided with a possibility for nominee-registration. Accordingly, they can choose a registration as a nominee name in which case it is impossible to separate these holdings from each other. Also all kind of indirect shareholdings are excluded from the data.

Table 4: Summary of the FCSD's trading data.

	Total turnover (M€)	Average turnover (k€)	Number of investors	Number of transactions (thousand)
Individual investors	104,989	15	338,053	7,234
Financial institutions	8,051,102	7,952	577	1,012
Non-financial institutions	252,681	238	19,134	1,063

The FCSD's data set contains 217 different stocks. However, we are going to introduce some requirements for the data and for this reason we are not able to use them all. Still, the data set is quite comprehensive since it contains nearly all major publicly traded Finnish companies. The investors can execute trades on many stock exchanges and all of these trades are recorded to the FCSD's register. In this study, we will only include those companies that are or have been listed in the Helsinki Stock Exchange.

Table 5: Summary of the stocks used in the study

Market Cap	Total turnover (M€)	Total volume (M€)	Average daily turnover (k€)	Average daily volume (k€)
Large	1,008,171	62,398	29,938	1,853
Other	65,030	9,641	554	82

The data set from Kauppalehti is a comprehensive data set also in a way that it contains all the stocks traded in Helsinki Stock Exchange from 1995 to the end of 2009. For these companies the data contains trading volumes, turnovers, closing prices and also adjusted closing prices that are used in the analysis later. Volume means the number of shares that changed hands during a given day. Similarly, turnover is the euro value of these shares. Closing price is the price quoted for each stock for each day when the stock closed. Adjusted closing price is similar but it takes into account all sorts of distribution that are made to investors and affect the price of the stock. These distributions can include stock splits, cash dividends and stock dividends.

Besides these two data sets, we have third data set that is containing information about news related to companies that were listed in the Helsinki Stock Exchange during the time period that our data is based on. The basic information about the news comes from OMX data base where all stock related news can be found. This database contains information about the date and heading of the news. However, it does contain same news with different languages. Most of the news related to stocks in Helsinki Stock Exchange are published in both Finnish and English and many times also Swedish. This creates duplicates of the news to the data. For this reason the data is manually reviewed. For each news item, several attributes are manually recognized. These attributes are related company, subject, language, whether or not news was scheduled, whether or not particular news item is the first release of that information, and whether or not news item revealed new information.

To be able to use all these data sets in same analysis we need to link them together. The FCSD's dataset contains ISIN number for each stock and so does the dataset from Kauppalehti so these data sources are linked together based on the ISIN number. However, the dataset containing news does not have the ISIN number. The news dataset only contains company's name which cannot directly be used to link the news data to other sources. For this reason, we create an ID number for each ISIN. Then we manually find the corresponding company name that is used in the OMX data. This way we assign an ID number for each news item that is corresponding to the IDs created for the ISINs.

Since there is a large amount of data, we have created a relational database to administer the data. We then run queries to produce the data in a panel data format separately for each of the analysis. The software used to administer database is MySQL. To run the panel data analysis, we use STATA that is widely known and has all the models that we need by default.

3.2 Theoretical Models and Methods

In this study, we will use different kinds of econometrics to gain understanding of the data. Here econometrics is defined as the *application of statistical techniques to problems in finance*. In this chapter we describe the models used later in the analysis.

3.2.1 Linear Regression

Regression analysis are very widely used tools to analyze econometrics. Regression is concerned with describing and evaluating the relationship between a given variable and one or more other variables. More specifically, regression is an attempt to explain movements in a variable by reference to movements in one or more other variables. Linear regression models enable us to model the relationship between a scalar dependent variable and one or more explanatory variables. When there is only one explanatory variable, the model is called simple linear regression. For more than one explanatory variables, the model is called multiple linear regression. In these models, data is modeled using linear predictor functions $f(i)$ that have the basic form of

$$f(i) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}, \tag{1}$$

where $\beta_0, \ldots, \beta_p$ are the coefficients indicating the relative effect of a particular explanatory variable on the outcome for data points $i = 1, \ldots, n$. (Brooks, 2014)

The most common method used to fit a line to the data is known as ordinary least squares (OLS). This approach forms the workhorse of econometric model estimation. If the errors are heteroscedastic, OLS estimators will still give unbiased coefficient estimates, but they no longer have the minimum variance among the class of unbiased estimators. If the form (i.e. the cause) of the heteroscedasticity is known, then an alternative estimation method which takes this into account should be used. One possible solution is called generalized least squares (GLS). If we suppose that the error variance was related to z_t by the expression

$$var(u_t) = \sigma^2 z_t^2. \tag{2}$$

then

$$var(v_t) = \sigma^2 \tag{3}$$

for known z, where

$$v_t = \frac{u_t}{z_t}. \tag{4}$$

(Brooks, 2014) This is the theoretical model linear regression models on which the calculations on this study are partly based on.

3.2.2 Event Study

To test the second hypothesis, that the trading of individual investors before an event is predicting the short-term abnormal returns of the stock after the event, we conduct an event study. We attempt to gauge the effects of scheduled and non-scheduled to the individual investors' trading behavior and whether or not they earn abnormal returns. To do this, we merge the FCSD's data set to the manually constructed data set that contains the information about news that have occurred during the period of interest.

We need to be able to define precisely the dates on which the events occur, and the sample data should usually be aligned with respect to this date. If we have N events in the data, we usually specify an 'event window', which is the period of time over which we study the impact of the event. The length of this window will be set according to our needs: whether we wish to investigate the short-term or long-term effects of the event. It is common to examine a period consisting of, for example, ten trading days before the event up to ten trading days after as a short-run event window, while long-run windows can cover a month, a year, or even several years after the event. (Brooks, 2014)

The first question to ask after the event has been identified is what frequency of data should be employed in the analysis. The power of event studies to detect abnormal performance is much greater when daily data is used rather than weekly or monthly observations, so that the same power can be achieved with a much smaller N, or for given N, the power will be much larger. In some cases it would be possible to use intra-daily data but this kind of data is harder to collect and may bring additional problems including nuisance microstructure effects. Still, most of the studies in the literature are using daily observations as the frequency of data. (Brooks, 2014)

We start by defining a measure that describes whether or not the trading of individuals have been abnormal and on which side. We call this measure the individual net trading measure. As in the Kaniel et al. (2012), we subtract the euro value of the shares sold by individuals from the euro value of shares bought by individuals and divide this by the average daily euro volume in the calendar year for the specific stock. This will gives us an imbalance measure. To get the individual net trading measure, we then subtract the daily average of the imbalance measure over the sample period. So for stock I on day t, we define $IndNT_{i,t}$ as

$$IndNT_{i,t} = Individual\ Imbalance_{i,t} - \frac{1}{T} \sum_{all\ days\ in\ 2006-2009} Individual\ Imbalance_{i,t}, \tag{5}$$

where

$$Individual\ Imbalance_{i,t} = \frac{(Individual\ buy\ euro\ volume_{i,t} - Individual\ sell\ euro\ volume_{i,t})}{Average\ daily\ euro\ volume\ in\ calendar\ year_{i,t}}. \tag{6}$$

We want to be able to study trading during several different time windows so we define cumulative abnormal net individual trading over the period $[t, T]$ as

$$IndNT^{i}_{[t,T]} = \sum_{k=t}^{T} IndNT_{i,k}, \tag{7}$$

where the period is defined relative to the date of the news (day 0).

To evaluate the connection between individual trading before the event to the cumulative abnormal returns, we need to calculate cumulative abnormal returns for different time windows for each stock. Market portfolio is constructed as equally weighted portfolio of the sample stocks and the cumulative returns of this market portfolio are subtracted from the cumulative stock returns. Specifically, we define adjusted cumulative return for stock *i* in a time period [*t*, *T*] as

$$AR^{i}_{[t,T]} = \left(\frac{P_{i,T} - P_{i,t}}{P_{i,t}}\right) - \left(\frac{MP_{i,T} - MP_{i,t}}{MP_{i,t}}\right), \tag{8}$$

where $P_{i,t}$ is the adjusted closing price of a stock *i* on a day *t* and similarly $MP_{i,T}$ is the adjusted closing price of the equally weighted stock portfolio.

We calculate the cumulative individual net trading for the following time windows: [-10, -11] and [-5, -1]. Similarly, we calculate the abnormal returns for the time windows of [0, 1], [2, 6], [2, 11], [2, 21], [2, 61] and [0, 61]. All of these figures are in relation to the date of the news (day 0). For each news we require that there are no other news that are related to the specific stock within the time windows presented above. This means that there will be less observations to study abnormal returns for [0, 61] than for [0, 1] since it is more likely that longer period is overlapping with other news.

To model the results, we use random effects model which helps us to control for unobserved heterogeneity when this heterogeneity is constant over time and when stock specific effects are uncorrelated with the independent variables. Because each week contains several news for different companies we correct the results for clustering. The dependent variable is abnormal return for certain time window and independent variable is cumulative individual net trading for certain time windows.

4. RESULTS

4.1 Individual net trading as a predictor for abnormal returns

We start by calculating the individual net trading measure according to equation 2 from the FCSD's data set. After this, we calculate the cumulative individual net trading measure for the following time windows: [-10, -1] and [-5, -1]. We also calculate the abnormal returns using the equation 5 for the time windows of [0, 1], [2, 6], [2, 11], [2, 21], [2, 61] and [0, 61].

We merge the data set from the calculations above with the news data. We implement one restriction to the news data: There needs to be at least 10 days of data before the event. Two different data sets are created: One to analyze the abnormal returns of individual investors around scheduled new and one to analyze the same connection around non-scheduled news.

First, we present the results for individual investor trading around scheduled news. We create a regression model using random effects where the dependent variable is adjusted returns and the independent variable is cumulative individual net trading. We also correct the results for clustering. Table 6 presents a summary of the data set used to analyze abnormal returns of individual investors around earnings announcements.

Table 6: Summary statistics for the data set used for analyses of abnormal returns around earnings announcements.

This table presents a summary statistics for the data set used for analyses of abnormal returns around earnings announcements. We report the number of observation and the number of stocks. We also report the minimum, maximum and average number of earnings announcements per stock during the sample period.

Number of observations:	1047
Number of stocks:	157
Observations per stock	
Min:	1
Avg:	6.7
Max:	13

Table 7 presents a summary of the descriptive statistics of the model where we use 5-day window for cumulative individual net trading.

Table 7: Descriptive Statistics for Cluster Corrected Random Effects Model using 5-day Window for Cumulative Individual Net Trading. (Earnings announcements)

This table presents the descriptive statistics for analysis of the linear correlation between individual investors trading before earnings announcements and the abnormal returns following the earnings announcement. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 5 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-5, -1]			
AR	Coefficient	z	P>z	R-sq overall
[0, 1]	0.0007279	1.11	0.266	0.0007
[2, 6]	-0.0002526	-0.29	0.773	0.0002
[2, 11]	0.0007269	0.54	0.586	0.0004
[2, 21]	-0.0029251	-1.41	0.158	0.0018
[2, 61]	0.0017495	0.53	0.593	0.0004
[0, 61]	3.07E-03	0.8	0.425	0.0013

We see that the results are statistically significant for none of the cumulative abnormal return windows used in the analysis. We can also see that the coefficient factors are really small through the analysis. These figures imply that the cumulative net trading from -5 days to -1 day prior to the announcement is not predicting the short-term abnormal returns of the stock no matter which time windows is used. These results are controversial to many other studies where results suggest that stocks bought by individual investors either go to earn positive abnormal returns[9] or negative abnormal returns[10].

Table 8 presents a summary of the descriptive statistics of the random effects model where we use 10-day window for cumulative individual net trading.

[9] See e.g (Kaniel et al., 2012, Kaniel et al., 2008, Kelley and Tetlock, 2013, Vieru et al., 2006)
[10] See e.g. (Andrade et al., 2008, Barber and Odean, 2000, Barber et al., 2009b, Hvidkjaer, 2008)

Table 8: Descriptive Statistics for Cluster Corrected Random Effects Model using 10-day Window for Cumulative Individual Net Trading. (Earnings announcements)

This table presents the descriptive statistics for analysis of the linear correlation between individual investors trading before earnings announcements and the abnormal returns following the earnings announcement. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 10 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-10, -1]			
AR	Coefficient	z	P>z	R-sq overall
[0, 1]	0.0002118	4.74	0.000	0.0017
[2, 6]	-0.000012	-0.18	0.857	0.0000
[2, 11]	-0.0005223	-5.44	0.000	0.0056
[2, 21]	-0.0006461	-5.11	0.000	0.0026
[2, 61]	-0.0002083	-0.56	0.579	0.0000
[0, 61]	-6.70E-06	-0.01	0.988	0.0000

Here we find statistically significant results for three of the time windows studied: [0, 1], [2, 11] and [2, 21]. AR[0,1] has a positive coefficient meaning that positive cumulative individual net trading in a 10-day windows before an earnings announcement positively predicts the cumulative abnormal returns of the stock in this time window. Interestingly the coefficient factors for AR[2, 11] and AR[2, 21] are negative meaning that the is a negative relationship with cumulative individual net trading and cumulative abnormal returns. These results are consistent with the ones from Barber et al. (2009b) who also report positive correlation on short horizon but negative on long horizon. Intuitive explanation for positive coefficient in a very short time-horizon could be that individual investors are providing liquidity to other investors and getting small compensation for that. This is also what Kaniel et al. (2012) reported when they divided the abnormal returns to two components: liquidity provision and informed trading. They report that about half of the returns are explained by liquidity provision. On the longer time-horizons, the compensation for liquidity provision is reversed by uninformed trading as has been documented by number of studies[11]. It should also be noted that the coefficients for the results are quite small meaning that the correlation is weak even though it is statistically significant.

[11] See e.g. (Andrade et al., 2008, Barber et al., 2009a, Barber et al., 2009b, Hvidkjaer, 2008)

After scheduled news, we present the results for individual investor trading around non-scheduled news. We create a regression model using random effects where the dependent variable is adjusted returns and the independent variable is cumulative individual net trading. We also correct the results for clustering. Table 9 presents a summary of the data set used to analyze abnormal returns of individual investors around non-scheduled news.

Table 9: Summary statistics for the data set used for analyses of abnormal returns around non-scheduled news.

This table presents a summary statistics for the data set used for analyses of abnormal returns around any kind of non-scheduled news. Because non-scheduled news can overlap with each other, we need to control for the overlapping. We require that the time interval from the news being analyzed to the next company's non-scheduled news is more than the time window for the cumulative abnormal returns in the particular analysis. Table reports the number of observation and the number of stocks for different conditions on how many days is required between sequential company news. We also report the minimum, maximum and average number of earnings announcements per stock during the sample period for each condition.

	Trading days to the next company news		
	> 11	> 21	> 61
Number of observations:	4068	2587	702
Number of stocks:	166	161	144
Observations per stock			
Min:	1	1	1
Avg:	24.5	16.1	4.9
Max:	49	28	11

Because non-scheduled news can occur at any sequence, we need to control for the time interval of news. We require that the time interval from the news being analyzed to the next company's non-scheduled news is more than the time window for the cumulative abnormal returns in the particular analysis. In practice, this means that we have less observation to analyze longer-term abnormal returns than we have for analyzing shorter-term abnormal returns.

Table 10 presents a summary of the descriptive statistics of the random effects model where we use 5-day window for cumulative individual net trading.

Table 10: Descriptive Statistics for Cluster Corrected Random Effects Model using 5-day Window for Cumulative Individual Net Trading. (Non-scheduled news)

This table presents the descriptive statistics for analysis of the linear correlation between individual investors trading before company news and the abnormal returns following the news. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 5 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-5, -1]			
AR	Coefficient	z	P>z	R-sq overall
[0, 1]	-8.99E-06	-0.18	0.856	0.0000
[2, 6]	-0.00013	-2.36	0.018	0.0002
[2, 11]	-7.5E-05	-1.04	0.296	0.0000
[2, 21]	-0.00021	-1.00	0.319	0.0001
[2, 61]	0.000595	2.54	0.011	0.0023
[0, 61]	5.03E-04	1.84	0.066	0.0014

Interestingly, we see opposite results for what we documented with earnings announcements. With non-scheduled news we see statistically significant results for AR[2, 6] of negative correlation and for AR[2, 61] for positive correlation. This implies that individual investors' trading prior to non-scheduled news is negatively correlated with the short-term abnormal returns but positively correlated with longer-term abnormal returns. This is interesting result and there might be several different reasons explaining the results. Non-scheduled news are surprises to investors so no preparation or analysis is done before them by institutional investors. It could be the case, that individual investors are familiar with the stocks as described in the chapter 2.1.3 hence making more informed investment decisions when there is no scheduled company news in the horizon. It might also be that individual investors are seeking sensations as described in chapter 2.1.2 which would mean that they take excessive risks and get small compensation for that from other investors if the risk is not realized.

Table 11 presents a summary of the descriptive statistics of the random effects model where we use 10-day window for cumulative individual net trading.

Table 11: Descriptive Statistics for Cluster Corrected Random Effects Model using 10-day Window for Cumulative Individual Net Trading. (Non-scheduled news)

This table presents the descriptive statistics for analysis of the linear correlation between individual investors trading before company news and the abnormal returns following the news. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 10 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-10, -1]			
AR	Coefficient	z	P>z	R-sq overall
[0, 1]	0.000126	1.68	0.092	0.0006
[2, 6]	2.87E-05	0.26	0.797	0.0000
[2, 11]	-9.3E-05	-0.69	0.492	0.0001
[2, 21]	-0.00025	-1.05	0.293	0.0003
[2, 61]	0.000394	1.07	0.286	0.0016
[0, 61]	4.34E-04	1.38	0.168	0.0016

Table 11 is providing evidence that the weak correlation that existed with IndNT[-5, -1] is not found when the time window prior to the event is extended. These results together with small coefficients in table 10 are providing evidence that individual investors' trading prior to non-scheduled news is not correlated with the abnormal returns after the event. These results together with the results from the table 10 could also be explained by inside trading which would explain why we see these results around non-scheduled news and more specifically few days before the news.

It is intuitive to think that individual investors might be somewhat more informed around company earnings announcements as they may be familiar with the stock or that they might be in better position than other investors to use the information they have due to their investment size. Other investors also might have stronger needs for immediacy around earnings announcements than non-scheduled news which is causing them to pay extra for liquidity provision of individual investors. This liquidity provision is not needed before non-scheduled news as the information is not available before the news. These factors could explain the results presented earlier.

To examine the robustness of the previous studies and also to potentially gain some further insight on the short-term abnormal returns of individual investors, we exercise another linear model to test the relation of individual net trading and abnormal returns. Be ignoring the news related to companies, we can calculate the net individual trading measure and abnormal returns for different time windows for every day that particular stock was traded. This gives us a lot more observations and enables us to confirm the results from the test above.

Again, we calculate the net individual trading measure and abnormal returns for different time windows. Now we don't merge this data with news data as we ignore the news announcements. Table 12 provides a summary of the data used for this analysis.

Table 12: Summary statistics for the data set used to analyze abnormal returns of individual investors without events.

This table presents a summary statistics for the data set used for analyses of abnormal returns without controlling for events. We report the number of observation and the number of stocks. We also report the minimum, maximum and average number of earnings announcements per stock during the sample period.

Number of observations:	127946
Number of stocks:	179
Observations per stock	
Min:	67
Avg:	714.8
Max:	990

Table 13 presents a summary of the descriptive statistics of the random effects model where we use 10-day window for cumulative individual net trading.

Table 13: Descriptive Statistics for Cluster Corrected Random Effects Model using 10-day Window for Cumulative Individual Net Trading. (No events)

This table presents the descriptive statistics for analysis of the linear correlation between individual investors trading and the abnormal returns following the trading without controlling for events. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 10 days before the day analyzed to 1 day before the day analyzed. Then we calculate the abnormal returns for each stock after the day analyzed. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-10, -1]			
AR	coefficient	z	P>z	R-sq overall
[0, 1]	-8.51E-06	-0.73	0.465	0.0000
[2, 6]	3.76E-05	1.26	0.207	0.0000
[2, 11]	0.000152	1.96	0.053	0.0002
[2, 21]	0.000242	1.81	0.070	0.0002
[2, 61]	0.000847	3.22	0.001	0.0009
[0, 61]	8.43E-04	3.22	0.001	0.0009

We see statistically significant results when considering monthly abnormal returns even though the correlation seems to be fairly week. However, the results are implying that individual investors do make informed investment decisions on longer time-horizons which gets very little support from the literature. Usually studies have found that individual investors do make informed investment decisions on the short time-horizon but not on the long time-horizon. This is interesting result and should be investigated further.

Table 14 presents a summary of the descriptive statistics of the random effects model where we use 5-day window for cumulative individual net trading.

Table 14: Descriptive Statistics for Cluster Corrected Random Effects Model using 5-day Window for Cumulative Individual Net Trading. (No events)

This table presents the descriptive statistics for analysis of the linear correlation between individual investors trading and the abnormal returns following the trading without controlling for events. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 5 days before the day analyzed to 1 day before the day analyzed. Then we calculate the abnormal returns for each stock after the day analyzed. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-5, -1]			
AR	coefficient	z	P>z	R-sq overall
[0, 1]	-1.62E-05	-0.84	0.403	0.0000
[2, 6]	-6.7E-05	-1.67	0.095	0.0000
[2, 11]	8.14E-05	1.3	0.195	0.0000
[2, 21]	0.000239	1.69	0.092	0.0001
[2, 61]	0.000882	3.44	0.001	0.0005
[0, 61]	8.68E-04	3.31	0.001	0.0004

Evidence from table 14 is quite similar to the evidence shown in table 13. It seems that there is weak but statistically significant correlation between cumulative individual trading and stock returns on a monthly horizon. For shorter horizons, such correlation is not found.

4.2 Cross-sectional performance of individual investors

To study the cross-sectional performance of individual investors, we use same data as we did in the previous study but we only include most active investors. We sort the investors based on the total number of transactions as we believe that transactions are better indicator of activity than volume. After sorting, we take 10 % of the investors with most transactions. This leaves us with little over 33 thousand individual investors.

First we present the results for active individual investor trading around scheduled news. We create a regression model using random effects where the dependent variable is adjusted returns and the independent variable is cumulative individual net trading. We also correct the results for clustering. Table 15 presents a summary of the data set used to analyze abnormal returns of active individual investors around earnings announcements.

Table 15: Summary statistics for the data set used for analyses of abnormal returns around earnings announcements with active investors.

This table presents a summary statistics for the data set used for analyses of abnormal returns around earnings announcements with active investors. We report the number of observation and the number of stocks. We also report the minimum, maximum and average number of earnings announcements per stock during the sample period.

Number of observations:	1041
Number of stocks:	155
Observations per stock	
Min:	1
Avg:	6.7
Max:	13

Table 16 presents a summary of the descriptive statistics of the model where we use 5-day window for cumulative individual net trading of active investors.

Table 16: Descriptive Statistics for Cluster Corrected Random Effects Model using 5-day Window for Cumulative Individual Net Trading of active investors. (Earnings announcements)

This table presents the descriptive statistics for analysis of the linear correlation between active individual investors trading before earnings announcements and the abnormal returns following the earnings announcement. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 5 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-5, -1]			
AR	Coefficient	z	P>z	R-sq overall
[0, 1]	0.0000252	0.05	0.957	0.0000
[2, 6]	0.0004631	-0.79	0.431	0.0004
[2, 11]	-0.0000936	-0.07	0.942	0.0000
[2, 21]	-0.0034229	-1.71	0.088	0.0024
[2, 61]	0.0000586	0.02	0.985	0.0000
[0, 61]	4.71E-04	0.14	0.889	0.0002

Table 16 is not providing any evidence of the correlation which is consistent with the results from all individual investors. However, it is not in line with the results from Vieru et al. (2006) who found that trading of the most active individual investors prior to the earnings announcements predicts short-term returns. Also many other studies have found that the trading of the most active traders might be predicting future returns[12].

Table 17 presents a summary of the descriptive statistics of the random effects model where we use 10-day window for cumulative individual net trading of active investors.

Table 17: Descriptive Statistics for Cluster Corrected Random Effects Model using 10-day Window for Cumulative Individual Net Trading of active investors. (Earnings announcements)

This table presents the descriptive statistics for analysis of the linear correlation between active individual investors trading before earnings announcements and the abnormal returns following the earnings announcement. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 10 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-10, -1]			
AR	Coefficient	z	P>z	R-sq overall
[0, 1]	0.0000252	0.05	0.957	0.0000
[2, 6]	-0.0003644	-0.79	0.431	0.0004
[2, 11]	-0.0000973	-0.14	0.887	0.0000
[2, 21]	-0.0010555	-1.00	0.319	0.0007
[2, 61]	0.0011422	0.70	0.481	0.0002
[0, 61]	1.49E-03	0.83	0.407	0.0006

Again, we see no statistically significant results. This is counterintuitive when considering the fact that we did find such correlation when considering all individual investors with the same parameters. It might be the case that active individual investors are not providing liquidity to other investors which would explain why we do not see positive correlation between trading prior to the event and positive abnormal returns on AR[0, 1].

After scheduled news, we present the results for active individual investor trading around non-scheduled news. We create a regression model using random effects where the dependent variable is adjusted returns and the independent variable is cumulative individual net trading. We also correct the results for clustering. Table 18 presents a summary of the

[12] See e.g. (Barber et al., 2011, Barber and Odean, 2000, Glaser and Weber, 2007, Grinblatt et al., 2012)

data set used to analyze abnormal returns of active individual investors around non-scheduled news.

Table 18: Summary statistics for the data set used for analyses of abnormal returns of active investors around non-scheduled news.

This table presents a summary statistics for the data set used for analyses of abnormal returns around any kind of non-scheduled news with active investors. Because non-scheduled news can overlap with each other, we need to control for the overlapping. We report the number of observation and the number of stocks for different conditions on how many days is required between sequential company news. We also report the minimum, maximum and average number of earnings announcements per stock during the sample period for each condition.

	> 11	> 21	> 61
Number of observations:	4002	2539	688
Number of stocks:	164	161	143
Observations per stock			
Min:	1	1	1
Avg:	24.4	15.8	4.8
Max:	49	28	11

Because non-scheduled news can occur at any sequence, we need to control for the time interval of news. We require that the time interval from the news being analyzed to the next company's non-scheduled news is more than the time window for the cumulative abnormal returns in the particular analysis. In practice, this means that we have less observation to analyze longer-term abnormal returns than we have for analyzing shorter-term abnormal returns.

Table 19 presents a summary of the descriptive statistics of the random effects model where we use 5-day window for cumulative individual net trading of active investors.

Table 19: Descriptive Statistics for Cluster Corrected Random Effects Model using 5-day Window for Cumulative Individual Net Trading of active investors. (Non-scheduled news)

This table presents the descriptive statistics for analysis of the linear correlation between active individual investors trading before company news and the abnormal returns following the news. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 5 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model

	IndNT [-5, -1]			
Adjusted Return	Coefficient	z	P>z	R-sq overall
[0, 1]	1.99E-05	0.16	0.872	0.0000
[2, 6]	-0.000203	-1.4	0.163	0.0002
[2, 11]	-0.000028	-0.08	0.937	0.0000
[2, 21]	-0.000846	-1.68	0.093	0.0004
[2, 61]	0.0022352	2.51	0.012	0.0038
[0, 61]	0.0019471	2.08	0.038	0.0025

Cumulative trading of active individual investors seems to have positive correlation with the positive abnormal returns on a monthly horizon. This is interesting as we did not see such correlation when considering all individual investors. These results are implying that active individual investors do better investment decisions before non-scheduled news than other investors. Maybe they keep themselves more informed about the company than other investors and are able to predict the following news. These results are in any case against the theory of efficient market and might even be implying that active investors have some insider information that others do not have.

Table 20 presents a summary of the descriptive statistics of the random effects model where we use 10-day window for cumulative individual net trading of active investors.

Table 20: Descriptive Statistics for Cluster Corrected Random Effects Model using 10-day Window for Cumulative Individual Net Trading of active investors. (Non-scheduled news

This table presents the descriptive statistics for analysis of the linear correlation between active individual investors trading before company news and the abnormal returns following the news. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 10 days before the event to 1 day before the event. Then we calculate the abnormal returns for each stock after the event. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model

	IndNT [-10, -1]			
Adjusted Return	Coefficient	z	P>z	R-sq overall
[0, 1]	0.0002626	1.56	0.120	0.0008
[2, 6]	0.0001784	0.7	0.485	0.0003
[2, 11]	0.0000819	0.31	0.758	0.0000
[2, 21]	-0.000123	-0.28	0.782	0.0000
[2, 61]	0.0022158	2.66	0.008	0.0070
[0, 61]	0.0023862	2.6	0.009	0.0069

The results in table 20 are similar to the ones in the table 19 but the coefficients are slightly higher implying stronger correlation. Further research needs to be done to examine why active individual investors do make better investment decisions on monthly horizon around non-scheduled news but same is not true around earnings announcements. This is not discussed in the current academic literature. One possible explanation is that institutional investors are trading more around earnings announcements and that they are even better informed than active individual investors.

As with all investors included, we examine the robustness of the results and also to potentially gain some further insight on the short-term abnormal returns of active individual investors, we exercise another linear model to test the relation of individual net trading and abnormal returns. By ignoring the news related to companies, we can calculate the net individual trading measure and abnormal returns for different time windows for every day that particular stock was traded. This gives us a lot more observations and enables us to confirm the results from the test above.

Again, we calculate the net individual trading measure and abnormal returns for different time windows. Now we don't merge this data with news data as we ignore the news announcements. Table 21 provides a summary of the data used for this analysis.

Table 21: Summary statistics for the data set used to analyze abnormal returns of active individual investors without events.

This table presents a summary statistics for the data set used for analyses of abnormal returns with active individual investors without controlling for events. We report the number of observation and the number of stocks. We also report the minimum, maximum and average number of earnings announcements per stock during the sample period.

Number of observations:	119130
Number of stocks:	170
Observations per stock	
Min:	67
Avg:	700.8
Max:	935

Table 22 presents a summary of the descriptive statistics of the random effects model where we use 10-day window for cumulative individual net trading of active investors.

Table 22: Descriptive Statistics for Cluster Corrected Random Effects Model using 10-day Window for Cumulative Individual Net Trading of active investors. (No events)

This table presents the descriptive statistics for analysis of the linear correlation between active individual investors trading and the abnormal returns following the trading without controlling for events. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 10 days before the day analyzed to 1 day before the day analyzed. Then we calculate the abnormal returns for each stock after the day analyzed. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-10, -1]			
Adjusted Return	Coefficient	z	P>z	R-sq overall
[0, 1]	-1.17E-05	-0.5	0.615	0.0000
[2, 6]	6.66E-05	1.16	0.247	0.0000
[2, 11]	0.000298	1.77	0.077	0.0003
[2, 21]	0.000562	1.95	0.052	0.0002
[2, 61]	0.001437	3.24	0.001	0.0011
[0, 61]	0.001439	3.2	0.001	0.0011

Table 22 documents similar results for active investors as we saw for all individual investors in table 13. However, the coefficients are a lot higher for active individual investors than they are for all individual investors. It might be the case that active individual investors are causing the correlation we saw in table 13. Future research should be done to determine whether or not non-active individual investors are trading in informed manner on monthly horizon.

Table 23 presents a summary of the descriptive statistics of the random effects model where we use 5-day window for cumulative individual net trading of active investors.

Table 23: Descriptive Statistics for Cluster Corrected Random Effects Model using 5-day Window for Cumulative Individual Net Trading of active investors. (No events)

This table presents the descriptive statistics for analysis of the linear correlation between active individual investors trading and the abnormal returns following the trading without controlling for events. We calculate the cumulative net individual trading balance using equation 4 for each stock. We use time-horizon from 5 days before the day analyzed to 1 day before the day analyzed. Then we calculate the abnormal returns for each stock after the day analyzed. Abnormal returns are analyzed for different time-horizons and the descriptive statistics for the model are presented on the table. We report the clustering corrected descriptive statistics for linear random effects model.

	IndNT [-5, -1]			
Adjusted Return	Coefficient	z	P>z	R-sq overall
[0, 1]	9.70E-06	0.24	0.808	0.0000
[2, 6]	-0.00012	-1.55	0.12	0.0000
[2, 11]	0.000094	0.76	0.449	0.0000
[2, 21]	0.000545	1.79	0.073	0.0002
[2, 61]	0.001467	3.22	0.001	0.0006
[0, 61]	0.001493	3.21	0.001	0.0006

As can be seen from the table 23, only the results for longer periods are statistically significant and also the coefficients are remarkable bigger for longer periods. These are exactly the same results that we also documented with IndNT[-10, -1] which is confirming the results in the table 22.

It seems that active individual investors are more informed in their investment decisions than their non-active peers. They trade better when not controlled for any events and also when controlled for non-scheduled company news. The only exceptions seems to be company earnings announcements. Around this type of events, cumulative active individual investors' trading seems not to be correlated in any way with the future abnormal returns.

5. DISCUSSION

We started the analysis by calculating the individual trading measure and abnormal returns for each stock and for each day in our sample data. We used several different time windows for both of these measures as we want to our results to be robust. We ran three different analyses where one was controlled for earnings announcements, on for non-scheduled news and on was not controlled for any events. For cumulative individual trading we use the following time windows: [-10, -1] and [-5, -1]. The former one represents two-week period and the latter one one-week period. These time windows are chosen based on the study of Kaniel et al. (2012). Longer time periods would not probably be useful as other factors than the ones under study would have great affect to the measures. For abnormal returns we use time windows of [0, 1], [2, 6], [2, 11], [2, 21], [2, 61] and [0, 61]. With these selection we can easily confirm the abnormal returns up to 61 trading days. These time windows are also in line with the study of Kaniel et al. (2012).

According to finance theories, the volatility is caused by new information. Since news contain a lot of public information that is available for all investor types, it is natural to study individual investors trading before news announcements and contrast this with the stock performance after the event. Our dataset contains the information whether or not particular news item was scheduled or not which gives us the opportunity to extend current literature. Most of the similar studies are using company earnings announcements as events for the study. Because we want our study to be comparable to those studies, we only use earnings announcements when we study scheduled news. For non-scheduled news, we don’t apply any restrictions related to the type of particular news.

We start our discussion with the results from analyzing scheduled news. Using 10-day window for cumulative individual trading prior to the earnings announcements, we did document weak correlation between investors buying (selling) a stock and positive (negative) abnormal returns during the day of the event and the following day. These findings are similar to the most of the studies conducted in the US. For example, Kaniel et al. (2012) document similar findings and conduct that the short-term abnormal returns are partly a compensation for liquidity provision and partly informed trading by individual investors. We do not divide abnormal returns into a liquidity provision component and informed trading component so we are unable to distinguish between the effects from these two components. Also the predictive power of cumulative individual investors’ trading is much weaker than what is documented by Kaniel et al. (2012). One possible explanation for weaker correlation could be the fact that Helsinki Stock Exchange has a lot less investors than New York Stock Exchange which also means less informed traders. Also the market is smaller and for that reason might not be able to attract the most informed traders.

When we consider longer time-horizons after the event, we get contrarian evidence to those reported by Kaniel et al. (2012). Our data shows that positive (negative) cumulative net individual trading prior to the earnings announcement is predicting negative (positive) abnormal returns after the event on a weekly horizon. One explanation could be that individual investors are not trading in an informed manner which would be consistent with the evidence from Andrade et al. (2008). Further research needs to be conducted to determine why the evidence from Kaniel et al. (2012) is different from ours. Different results might be explained by NYSE having more informed traders as it has higher volumes and larger number of stocks.

The results for scheduled news are intriguing. Why do we find correlation when we use longer time horizon for cumulative individual net trading while there seem to be no correlation for shorter time horizon? One possible explanation is that institutional investors are repositioning themselves over one week before the earnings announcement and individual investors are providing liquidity. It is also interesting to see that for IndNT[-10, -1] the relationship is positive at very short time horizon but negative at little longer time horizons after the announcement. Intuitive explanation to this result would be that individual investors are providing liquidity for other investors. For this liquidity provision, they earn small abnormal returns on a very short horizon. On a little longer horizon, individual investors earn negative abnormal returns due to uninformed investment decisions. These results are similar to Barber et al. (2009b) who report positive relation on short horizon and negative relation in longer horizon. However, they define longer horizon to be 2 to 12 months.

Interestingly, when we consider only the most active investors, we see no correlation of any kind between cumulative net individual investors' trading and future abnormal returns. Together with prior evidence, it could be the case that most active investors are not providing liquidity to other investors and thus not getting positive instant abnormal returns but also not consistently earning negative abnormal returns on weekly horizon. In any case, these results are opposite to the ones reported by Vieru et al. (2006) who report that trading of most active individual investors prior to the earnings announcements predicts short-term returns. One possible explanation for the difference might be the different methodologies used in the studies.

When considering the non-scheduled news, we saw evidence that individual investors earn negative abnormal returns on the following week after the event but positive returns on monthly horizon. These results are implying that individual investors might be trading in an informed manner when considering longer time-horizons. The correlation seems to be extremely weak but statistically significant. These results are consistent with the ones from US both not with most of the studies done in other countries where individual investors are seen as uninformed investors. In the literature, only the most active or most intelligent investors are described as informed investors and we also saw stronger positive correlation when considering only the most active individual traders. This implies that most active investors are doing better investment decisions but we do not know whether or not they can cover higher transaction costs with the informed trading. Future research should be conducted where the transactions costs are also considered to determine whether or not the most active individual investors earn better returns than other individual investors.

The question why cumulative net individual trading prior to the event has different kind of effects on cumulative returns around scheduled news and non-scheduled news needs further research. However, we have found evidence that cumulative net individual trading prior to an event does predict the cumulative abnormal returns after the event. The link is weak but still statistically significant and similar results were found when considering the link without controlling for events.

The results provide evidence that individual investors can earn positive abnormal returns but the significance of these results needs further investigation. Around earnings announcements, the very short-term positive relationship could be explained by the liquidity provision role of individual investors which would enable them to earn small abnormal returns for providing liquidity to other investors. Further research is needed to determine why we see exact opposite results for non-scheduled news.

6. CONCLUSION

This study provides important evidence to the academic discussion around individuals as investors and their performance in the stock market. The results are somewhat similar to the ones reported in the US where several studies have shown that individual trading can predict future returns of the stocks. However, we found much weaker correlation than what has been found in the US.

The results suggest that cumulative net individual trading prior to an event does predict the cumulative abnormal returns after the event but the link is quite weak and varies when different time-horizons are used or only active individual investors are considered. The results show a positive correlation between individual investors buying stocks prior to earnings announcement and the positive abnormal returns of the stock on the day of the event and on the following day. This correlation turns to be negative when we con-sider longer time periods for abnormal returns. With non-scheduled news, we did not find such correlation when considering all individual investors but correlation was found when we considered only the most active individual investors. When we did not control for any kind of events, we found that individual investors seem to be investing in an informed way.

Kaniel et al. (2012) and Kaniel et al. (2008) both report that the trading of individual investors prior to the event does predict the abnormal returns of the stock. However, Kaniel et al. (2012) and Kaniel et al. (2008) report that positive cumulative individual net trading prior to the event is predicting positive abnormal returns no matter if daily, weekly or monthly time-horizons are used. On the other hand, our study suggests that this correlation is changing from positive to negative when daily time-horizon is expanded to monthly time-horizon. The difference between results could be explained with the methodologies used in each study or with the fact that investors and/or markets are different in the US from the ones in Finland.

Vieru et al. (2006) are also studying data from Finland. However, they use a data set that consist of older data than ours. They report that the trading of the most active individual investors prior to the earnings announcements predicts short-term returns. This is opposite to the results that we got. We report that trading of *all* individual investors does predict abnormal returns but we were unable to find similar link with the most active individual investors. The differences could be explained by the methodologies used in the studies. Still, future research is needed.

Even though we did find evidence of informed individual trading when we did not control the study for any events, we are unable to discuss whether or not individual investors can earn abnormal returns when the transaction costs are taken into account. Most of the prior studies report that individual investors are earning negative returns after transactions costs. Future research needs to be done to determine the returns earned by individual investors using our data set when transaction costs are taken into account.

This study has raised several topics for future research. We found evidence that active investors are trading in an informed way so it needs to be investigated further if non-active individual investors are also trading in informed manner on monthly horizon. It is also uncertain if the most active individual investors earn better abnormal returns than other individual investors when transaction costs are taken into account. Further research should also determine why our study shows that trading of the most active individual investors does not predict abnormal returns after earnings announcements while Vieru et al. (2006) report that it does even though data from same stock market was used. Finally it needs to be investigated do individual investors earn positive returns from trading when transaction costs are taken into account.

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